

Results of the AutoML challenge

Isabelle Guyon, Imad Chaabane, <u>Hugo Jair Escalante</u>, Sergio Escalera, Damir Jajetic, James Robert Lloyd, Nuria Macia, Bisakha Ray, Lukasz Romazco, Michele Sebag, Alexander Statnikov, Sebastien Treger, Evelyne Viegas

automl@ChaLearn.org

Challenges in Machine Learning





Thanks

Hackathon team: Marc Boullé Lukasz Romaszco Sébastian Treger Emilia Vaajoensuu Philippe Vandermersch

Software development:

Eric Carmichael Ivan Judson Christophe Poulain Percy Liang Arthur Pesah Xavier Baro Solé Lukasz Romaszco Michael Zyskowski

Advisors and beta testers: Kristin Bennett Marc Boullé

Cecile Germain Cecile Capponi Richard Caruana Gavin Cawley Gideon Dror Sergio Escalera Tin Kam Ho Balasz Kégl Hugo Larochelle Víctor Ponce López Nuria Macia Simon Mercer Florin Popescu Michèle Sebag Danny Silver,

Codalab management:

Evelyne Viegas Percy Liang Erick Watson



ChaLearn board

Data providers:

Yindalon Aphinyanaphongs Olivier Chapelle Hugo Jair Escalante Sergio Escalera Zainab Iftikhar Malhi Vincent Lemaire Chih Jen Lin Meysam Madani Bisakha Ray Mehreen Saeed Alexander Statnikov Gustavo Stolovitzky H-J. Thiesen Ioannis Tsamardinos

Result analysis: Imad Chaabane



INTRODUCTION

Challenges in Machine Learning





The REALITY





ChaLearn ML challenges





AutoML challenge





What's exciting?

- Intellectually challenging:

- Completely autonomous learner
- Beat the "no free lunch theorem"
- Model selection
- Meta learning
- Two-level objectives
- Any overall objective (R², ABS, BAC, AUC, F1, PAC)
- Any time
- Practically important:
 - Improve cost effectiveness
 - Improve reliability
 - Reach out to more applications



CHALLENGE DESIGN

Challenges in Machine Learning



Data: 30 large datasets

																	Т	$\mathbf{\nabla}$	1	u (31	1 2	-
						-						,	-				<u></u> ζ	2	<u>n </u>	03	5 4	12	2
		httr	$\cdot / 2$	hit	on	าไ	ch	nale	29r	n	n r	σ/c	lat	3			F		-		\pm		
				uu		<u>п.</u>		lan		11.		5/1	ıaı	<u>a</u>			S.	5	7	5 4	5 4	15	4
		_															R.	C	Le	26	<u> -</u>	<u>يد</u> د	ž
The Very Least American State																	<u>ر</u> .	2	-1	-	<u>-</u> +-	44	~
A Contraction of																	5	5	36	0 8	<u>7</u> \$	821	2
			1															1	n.	2	1 0	20	0
	Ind Num	Name	Task	Metric	Time (Cnum (Cbal	Sparse	Missng (Catvar I	rrvar	Pte	Pva	Ptr	N	Ptr/N		$ \tau $				<u> </u>	<u> </u>
	0	1 ADULT	multilabel	F1	300	3	1	0.16	0.011	1	0.5	9768	4884	34190	24	1,424.58		28		14	1 13	Mar a St	-
	0	2 CADATA	regression	R2	200	0	NaN	0	0	0	0.5	10640	5000	5000	16	312.5					1		694 -
Standard I -	0	3 DIGITS	multiclass	BAC	300	10	1	0.42	0	0	0.5	35000	20000	15000	1568	9.57		50.		1856	1 B		-
	0	4 DOROTHEA	binary	AUC	100	2	0.46	0.99	0	0	0.5	800	350	800	100000	0.01				12		A	de.
A TOTAL	0	5 NEWSGROUPS	multiclass	PAC	300	20	1	1	0	0	0	3755	1877	13142	61188	0.21		13		1	1		
	1	1 CHRISTINE	binary	BAC	1200	2	1	0.071	0	0	0.5	2084	834	5418	1636	3.31		12		100	<u>6.</u>		S. 2
12	1	2 JASMINE	binary	BAC	1200	2	1	0.78	0	0	0.5	1756	526	2984	144	20.72	0.00						a an
	1	3 MADELINE	binary	BAC	1200	2	1	1.2 E-06	0	0	0.92	3240	1080	3140	259	12.12	0.00			inne j	4		3.00
La series and a series of the	1	4 PHILIPPINE	binary	BAC	1200	2	1	0.0012	0	0	0.5	4664	1166	5832	308	18.94		100	(illing)	dunth		AL AN	
A BARY	1	5 SYLVINE	binary	BAC	1200	2	1	0.01	0	0	0.5	10244	5124	5124	20	256.2		-	Aure				
S CALCO	2	1 ALBERT	binary	F1	1200	2	1	0.049	0.14	1	0.5	51048	25526	425240	78	5,451.79				-			
	2	2 DILBERT	multiclass	PAC	1200	5	1	0	0	0	0.16	9720	4860	10000	2000	5						20.	
Charles and the	2	3 FABERT	multiclass	PAC	1200	7	0.96	0.99	0	0	0.5	2354	1177	8237	800	10.3		13	 I 	10		ΨQ.	
	2	4 ROBERT	multiclass	BAC	1200	10	1	0.01	0	0	0	5000	2000	10000	7200	1.39		sci *		news	-	alt *	
- ALEC-	2	5 VOLKERT	multiclass	PAC	1200	10	0.89	0.34	0	0	0	7000	3500	58310	180	323.94			-	incino.			
2040	3	1 ALEXIS	multilabel	AUC	1200	18	0.92	0.98	0	0	0	15569	7784	54491	5000	10.9				الملق ا		C	
	3	2 DIONIS	multiclass	BAC	1200	355	1	0.11	0	0	0	12000	6000	416188	60	6.936.47		11		P		39	
	3	3 GRIGORIS	multilabel	AUC	1200	91	0.87	1	0	0	0	9920	6486	45400	301561	0.15			-	mina	-		
	3	4 JANNIS	multiclass	BAC	1200	4	0.8	7.3 E-05	0	0	0.5	9851	4926	83733	54	1,550,61		comp.		misc.		rec.	
	2	E WALLES		4110	1200		0.01		0			0100	4000	10000	102721	0.05						60	
	3	5 WALLIS	multiclass	AUC	1200	11	0.91	1	U	0	0	8196	4098	10000	193/31	0.05		66 7	2	1 P			
	4	1 EVITA	binary	AUC	1200	2	0.21	0.91	0	0	0.46	14000	8000	20000	3000	6.67		<u> </u>					
	4	2 FLORA	regression	ABS	1200	0	NaN	0.99	0	0	0.25	2000	2000	15000	200000	80.0		2		TY			
	4	3 HELENA	multiclass	BAC	1200	100	0.9	6 E-05	0	0	0	18628	9314	65196	27	2,414.67		40		- 1a	Sec	A SI	S. A
	4	4 TANIA	multilabel	PAC	1200	95	0.79	1	0	0	0	44635	22514	157599	4/236	3.34	611			F	1		SEA.
	4	5 YOLANDA	regression	R2	1200	0	NaN	1 E-07	0	0	0.1	30000	30000	400000	100	4000		1	11	1	9	- AP	
	5	1 ARTURO	multiclass	F1	1200	20	1	0.82	0	0	0.5	2733	1366	9565	400	23.91	- Freite	A Date	Rand				and and
	5	2 CARLO	binary	PAC	1200	2	0.097	0.0027	0	0	0.5	10000	10000	50000	1070	46.73	ante a	- Read	-		-	-	a los
- W	5	3 MARCO	multilabel	AUC	1200	180	0.76	0.99	0	0	0	20482	20482	163860	15299	10.71	6	-		-	4	and the second	ST.
AMA MA	5	4 PABLO	regression	ABS	1200	0	NaN	0.11	0	0	0.5	23565	23565	188524	120	1,571.03	1 A.	-	100	-	-		100
Wer lat	5	5 WALDO	multiclass	BAC	1200	4	1	0.029	0	1	0.5	2430	2430	19439	270	72		2	GI		1		
1-1-1-																		25	10	1	19	and the second	K X
al and the second second																			-	2.06			123
									_					_		B	1000				ALC: NO.	ALC: NO.	

Challenges in Machine Learning

http://chalearn.org

401060-3





- **INPUT** = **I.I.D.** data in feature representation, but:

- Sparse or full matrices.
- Numerical/categorical/binary variables.
- Missing values or not.
- Noisy data or not.
- Various proportions Ntrain / Nfeat.
- **OUPUT** = one target, but:
 - Binary (two-classes, balanced or not).
 - Categorical (multi-class: tens, hundreds of classes)
 - Multi-label.
 - Regression.
- **OBJECTIVE** = miscellaneous loss funtions.
- **COMPUTATIONAL RESOURCES** = fixed (20 min on 8 core x84_64).







- **1. NOVICE:** Binary classification.
- 2. INTERMEDIATE: Multiclass classification.
- **3. ADVANCED:** Multiclass and multilabel.
- 4. **EXPERT:** Classification and regression.
- **5. MASTER:** All of the above.

 AutoML: Automatic code execution on Codalab platform.

- **Tweakathon:** Result or code submission.
- To earn prizes:
 code should be
 made open
 source.

















Challenges in Machine Learning



RESULTS

Challenges in Machine Learning



Influence of the starting kit

- Python example using scikit-learn: most people used it to get started.
- Many top ranking participants (including aad_freiburg) used scikit-learn.
- Codalab platform accepted:
 - Python scripts.
 - Linux executables.
 - Java JRE executables.
- C code: ideal.intel.analytics; Marc Boulle.



Fact Sheets (28 responses)





Dimensionality reduction



Challenges in Machine Learning



PREDICTOR:



Challenges in Machine Learning





Challenges in Machine Learning



Algorithmic complexity

Qualitative advantages



Challenges in Machine Learning





Challenges in Machine Learning











Everybody

Challenges in Machine Learning



Best overall AutoML: aad_freiburg

		AutoN	ΛL						
Rnd	Ended	Winners	< R >	$ \langle S \rangle $	Ended	Winners	< R >	$ \langle S \rangle $	UP (%)
						1. ideal	1.40	0.8159	
0	NA	NA	NA	NA	02/14/15	2. abhi	3.60	0.7764	NA
						3. aad	4.00	0.7714	
		1. aad	2.80	0.6401		1. aad	2.20	0.7479	
1	02/15/15	2. jrl44	3.80	0.6226	06/14/15	2. ideal	3.20	0.7324	15
		3. tadej	4.20	0.6456		3. amsl	4.60	0.7158	
		1. jrl44	1.80	0.4320		1. ideal	2.00	0.5180	
2	06/15/15	2. aad	3.40	0.3529	11/14/15	2. djaj	2.20	0.5142	35
		3. mat	4.40	0.3449		3. aad	3.20	0.4977	
		1. djaj	2.40	0.0901		1. aad	1.80	0.8071	
3	11/15/15	2. NA	NA	NA	02/19/16	2. djaj	2.00	0.7912	481
		3. NA	NA	NA		3. ideal	3.80	0.7547	
		1. aad	2.20	0.3881		1. aad	1.60	0.5238	
4	02/20/16	2. djaj	2.20	0.3841	05/1/16	2. ideal	3.60	0.4998	31
		3. marc	2.60	0.3815	and the second second second	3. abhi	5.40	0.4911	
G						1. abhi	5.60	0.4913	
Р	NA	NA	NA	NA	05/1/16	2. djaj	6.20	0.4900	NA
U						3. aad	6.20	0.4884	
		1. aad	1.60	0.5282					
5	05/1/16	2. djaj	2.60	0.5379	NA	NA	NA	NA	NA
		3. post	4.60	0.4150					

aad=aad_freiburg abhi=abhishek4 asml=amsl.intel.com djaj=djajetic ideal=ideal.intel.analytics jlr44 = backstreet.bayes marc=marc.boulle mat=matthias.vonrohr post = postech.mlg_exbrain ${\tt tadej=tadejs}$

Challenges in Machine Learning



POST-CHALLENGE ANALYSIS

Challenges in Machine Learning



Last submitted code average on all 30 datasets



Challenges in Machine Learning



Results per dataset



Challenges in Machine Learning



Nothing salient



Challenges in Machine Learning





Challenges in Machine Learning





Challenges in Machine Learning





Challenges in Machine Learning





Challenges in Machine Learning





Challenges in Machine Learning



Heterogenous ensembles or single type of classifier?



Challenges in Machine Learning



Conclusion

- We have made great progress, but there is still a "gap": Tweakathons get about 30% better than AutoML.
- Free Auto-sklearn thanks to aad_freiburg (thanks!)
- The gap is not so big, we are almost there, but we could make the tasks harder (unpreprocessed data, non i.i.d. data, etc.)
- The challenge is hopefully the first in a series: moving towards life long AutoML and adversarial AutoML.

More on http://automl.chalearn.org/





Beat AutoSKlearn game @WCCI16

- July 24 July 26, 2016: Fun machine learning game!
- Try to beat the winners of the AutoML challenge by manually tweaking hyperparameters.
- <u>http://autosklearn.codalab.org</u>





Beat AutoSKlearn game @WCCI16

Your Machine Learning Pipeline Configuration

 A friendly GUI for (manual) configuration generation & submission was
 provided by the aad_freiburg team and ChaLearn

preprocessor	pca	0	()
pca:keep_variance	0	0.85	٩
pca:whiten	True	0	١
classifier	random_forest	0	1
random_forest:min_samples_split	0	2	
random_forest:criterion	gini	6	
random_forest:max_features	-0	0.99	٢
random_forest:min_samples_leaf	0	1	١
random_forest:bootstrap	True	0	١
DOWNLOAD SUBMISSION!		2. SUBMIT COM	NFIGURATIO



Challenges in Machine Learning



Was AutoSKlearn beat?

• No! Yet

	licor	Score
	User User	-300E
1	AUTOSKLEARN	0.7815 (1)
2	borbudak	0.7544 (2)
3	lisa	0.7507 (3)
4	brunoseznec	0.7372 (4)
5	djajetic	0.6921 (5)
б	Krxsy	0.6643 (6)
7	finlouarn2	0.6502 (7)
в	FlyingFox	0.6350 (8)
9	smohsinali	0.6108 (9)
10	lise_sun	0.5989 (10)
11	aaron	0.4935 (11)
12	hugo.jair	0.4585 (12)
13	Guru	0.3905 (13)
14	pellegrin	0.1957 (14)
15	a.morales	0.1245 (15)
16	aems30	0.0958 (16)

Challenges in Machine Learning



Was AutoSKlearn beat?

- The game was open for a very short period (48hours)
- Half of the participants submitted random-models
- Top ranked participants were very close to the AutoML winner, yet it was not beaten
- It will be interesting to open the game for more time and give it more dissemination so that AutoSKlearn can be really challenged!



Beat AutoSKlearn game @WCCI16

- Will remain open for a few days
- We will organize a coopetition around it
- Please participate, disseminate!
 - <u>http://autosklearn.codalab.org</u>





Results of the AutoML challenge

- Isabelle Guyon, Imad Chaabane, <u>Hugo Jair Escalante</u>, Sergio Escalera, Damir Jajetic, James Robert Lloyd, Nuria Macia, Bisakha Ray, Lukasz Romazco, Michele Sebag, Alexander Statnikov, Sebastien Treger, Evelyne Viegas
- automl@ChaLearn.org



Challenges in Machine Learning



Beat AutoSKlearn game WCCI16

Your Machine Learning Pipeline Configuration

rescaling	standardize	0	1
preprocessor	pca	ð	١
pca:keep_variance	0	0.85	١
pca:whiten	True	0	١
classifier	random_forest	0	١
random_forest:min_samples_split	0	2	(1)
random_forest:criterion	gini	3	١
random_forest:max_features	-0	0.99	٢
random_forest:min_samples_leaf	0	- 1	1
random_forest:bootstrap	True	0	١
1. DOWNLOAD SUBMISSION!		2. SUBMIT COM	IFIGURAT
		3. VIEW LI	ADERBO

IEEE WORLD CONGRESS ON COMPUTATIONAL INTELLIGENCE 24-29 JULY 2016, VANCOUVER, CANADA

Beat Auto-Sklearn @ WCCI2016

July 24 - July 26, 2016: Fun machine learning game! Try to beat the winners of the AutoML challenge by manually tweaking hyper-parameters.

AutoSklearn is a novel solution for autonomous machine learning that recently won the ChaLearn AutoML competition,. AutoML focused in developing automatic methods to solve a variety of supervised learning problems without any human intervention. Methods for AutoML, including AutoSklearn, aim at taking the human expert out of the loop, are you going to allow this?



Please visit the challenge website to participate (it's embarrassingly easy): http://autosklearn.codalab.org

The challenge will be open to anyone from July 24 to July 26 (results will be announced on July 26 during the contest session of WCCI AutoML Challenge II at Vancouver, Canada).

ML4AAD

0000 СНА

EARN

Contact: autosklearn@chalearn.org

> 0 0

Challenges in Machine Learning